The art of prompt engineering as an old/new form of dialogic information seeking using artificial intelligence models

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Abstract

Purpose/Thesis: The article synthesises theoretical and practical considerations of dialogic communication with artificial intelligence, focusing on established information retrieval models. It explores the interdisciplinary nature of information behaviour research and the evolution of retrieval models.
Approach/Methods: A qualitative methodology incorporated critical literature analysis and a case study using ChatGPT to search scientific literature.
Results and conclusions. The analysis revealed interdependencies between traditional and modern models, emphasising cognitive and exploratory aspects of information retrieval.
Research limitations: Focuses on specific prompt engineering models and a singular case study.
Practical Implications: Understanding established models is crucial for developing prompt engineering.
Originality/Value: This study addresses a gap in research on integrating information retrieval models with prompt engineering.

Keywords

Artificial Intelligence (AI). ChatGPT. Conversational Information Retrieving. Dialogic Approach. Information Seeking Model. Information Searching. Prompt Engineering (PE)

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1. Introduction

This article addresses the issue of modelling conversation and conducting a dialogue between humans and machines. Despite the assumption that new technologies and continuously evolving interaction patterns between humans and computers are being developed, the reality is apparent: this is merely an extension and

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refinement of existing communication patterns in information science and the dialogical model of information retrieval in the relationship between humans and computers.

Dialogue systems mimic human conversation, ranging from simple chatbots to more complex components like video game NPCs, which interact with players through dialogue. These systems function as decision trees, where user input triggers specific responses (Pisarski, 2024, p.230). Conversational systems can be categorised into two types: tool systems, designed for efficiency and accuracy, and anthropomorphic systems, which simulate human-like interaction to foster emotional engagement. The latter plays a crucial role in information-seeking models, aiding users in discovering and constructing context through intuitive exploration (Chen J. et al., 2024; Zhou et al., 2024).

Integrating patterns derived from interaction in dialogue systems and information-seeking behaviour will undoubtedly facilitate the evolution of conversational systems beyond their current role as mere information-seeking tools. They must and will act as intermediaries in dynamic, user-centred information landscapes. The conversation influences the user's understanding and experience of the information sought in these landscapes.

The prompt engineering literature highlights clear correlations, focusing on developing and optimising prompts to utilise language models effectively. User experience principles, like Nielsen's heuristics, should be considered when designing conversational systems, particularly in aligning system language with the user's context. Defining the task, formality, and specialist terms is essential for reliability (McNulty, 2024), and prompts must be user-friendly (Springs, 2024). Language, tone, and style should ensure inclusivity, with frameworks like Persona or Audience Persona Patterns helping to tailor systems to user profiles (Corral, 2023). Challenges include linguistic flexibility, representing diverse users, and avoiding over-generalisation. Prompt engineering is closely linked to AI literacy, requiring an understanding of how inputs affect outputs (Bates, 2024; Lund, 2023). Information and digital literacy are crucial when managing generative AI (Zhang, 2024), especially to avoid AI hallucinations—false outputs triggered by tricky queries (Pisarski, 2024). Strategies like handling missing data (Ruksha, 2024; Srinivasan, 2024) can reduce hallucinations but require advanced AI knowledge. Tools like ChatGPT allow users to conduct complex analyses without expertise, raising concerns about safety and reliability. The ACRL's information literacy framework emphasises critical evaluation of AI results (Hall & McKee, 2024), especially in AI-assisted library services where librarians need GenAI skills. Controlled vocabulary use, personality trait analysis via lexical tools like DesPrompt (Wen et al., 2023), information extraction from documents (Yuan et al., 2023), and recommender systems design (Zixuan Yi et al., 2024) underscore the integration of information science with prompt engineering.

There is growing interest in information retrieval principles of relevance, completeness, and accuracy. To elicit creative responses, prompts must be clear and unambiguous and encourage open-ended replies (McNulty, 2024; Springs, 2024). Moreover, prompts must be pertinent to the interaction. They facilitate discourse, aligning with user objectives. Well-crafted prompts are key to meaningful interactions in dialogue systems. This article concerns the pivotal elements of prompt engineering and their interconnection with selected models in information behaviour and retrieval.

2. Conceptual framework

Information seeking and searching is part of the broader spectrum of human information behaviour. Information seeking is an intentional search for relevant information that addresses specific needs (Case & Given, 2016; Cisek, 2017; Savolainen, 2017). The stages and activities involved in this process are also subordinate to broader information behaviour, occurring in various contexts and interactions between humans and technology, such as computers, search systems, or AI models (Krakowska, 2022). Establishing a theoretical basis for understanding the interdependence of information-seeking patterns and prompt engineering is crucial for evaluating the hypothesis.

2.1. Information seeking, searching and retrieving

It is essential to understand comprehensively the processes involved in information retrieval, particularly concerning their interaction with artificial intelligence models and the principles that underpin them. That should be contextualised within broader information-seeking models, which have been extensively researched. The term "retrieval" is often used imprecisely, so clarifying and differentiating the terminology is important. Information behaviours involve multidirectional activities related to sources, channels, and information systems. These include recording, seeking, interpreting, and using information (Fidel, 2011; Ford, 2015). These behaviours can be categorised into intentional and iterative processes, including information seeking, searching, and retrieving, aimed at solving problems and tasks effectively.

In the context of human-computer interactions, information exploratory searching is a crucial aspect of information behaviour. This process includes several activities related to information seeking. The compilation, verification and resolution of queries comprise this process. Exploratory searching is an integrated learning process. Learning is the process of acquiring, comparing and integrating knowledge.

This search is exploratory. Accretion involves enhancing and structuring knowledge through various processes (Marchionini, 2006). This exploratory model addresses complex problems and enhances cognitive capacities in individuals through symbiotic relationships between humans and computers, which identify information landscapes. This exploratory mode of information retrieval engages with resources to foster new knowledge (White & Roth, 2009; Materska, 2020).

Information seeking is the cognitive effort to gain insight, involving searching for accurate information, questioning, or scanning the environment (Thani & Hashim, 2011). It is a form of problem-solving that includes identifying, interpreting, and evaluating information with potential repetition (Marchionini, 1989).

In contrast, information searching focuses on acquiring specific information from particular sources, often online. That involves query formulation and evaluating the relevance of results, with both observable system actions and unobservable cognitive processes at play (Bawden & Robinson, 2012; Spink & Cole, 2006; Spink & Dee, 2007).

Information retrieval, a subset of searching, extracts information using retrieval systems on databases or web resources. It synchronises queries with search terms and results but does not consider user context or the complexity of their information needs (Lin, 2017). Maria Próchnicka defines information retrieval as a multidirectional interaction that transforms the user's knowledge asymmetry by generating complete and relevant information based on the user's needs (Próchnicka, 2004). She highlights that key components in modelling information retrieval behaviour are system performance and individual cognitive features, which shape how queries are formulated and processed. This dialogue with the system integrates and modifies knowledge while addressing or generating new information needs (Próchnicka, 2004; 2001; 2002). Query formulation and result evaluation are tied to problem identification, information extraction, and scanning (Ellis, 1989; 1992; Bates, 1989; Marchionini, 2006). Interactive information retrieval, involving communication between the user, intermediary, and system, supports both conversational and dialogic models of information seeking and links to conversational prompt engineering (Ingwersen, 1992).

Conversational models, which view dialogue as the foundation of human-computer interaction, have long been developed in information science, particularly within information behaviour research. Foundational models by Garry Marchionini and Nicholas Belkin in the 1990s identified key stages in the information retrieval process. Later models, such as those by Marcia Bates (1990; 1999), David Ellis (1989; 1992), Maria Próchnicka (2004), and Reijo Savolainen (2016; 2019), have evolved alongside advancements in information systems and AI. These earlier models form the basis of modern prompt engineering, reflecting expressive and creative information-seeking approaches (Fredrick, 2024; Zhang, 2023). Prompt engineering, a form of query-based interaction, uses patterns learned from natural language to interpret human input, highlighting the fluid and adaptive nature of human-AI communication, including how search queries are refined based on results.

Belkin's concept posits that human interaction with text is active, as individuals seek, engage with, and interpret texts to make meaning and achieve goals (Belkin & Cool, 1993; Belkin & Marchetti & Cool, 1993). This interaction is part of information-seeking behaviour, where people search for texts or advice to resolve knowledge gaps. Garry Marchionini's (1995) information-seeking model outlines eight stages: recognising, comprehending, selecting, formulating, executing, examining, extracting, reflecting, reiterating, and ceasing. The model shows how information is extracted and integrated with existing knowledge. Marchionini also identifies three types of browsing – directed, semi-directed, and undirected – alongside factors that influence search behaviour, such as the searcher, task, system, and context. Belkin and Marchionini's models underpin the dialogical model of information seeking, correlating human cognitive, informational, and emotional processes with system engagement. Figure 1 shows the proposed integrated scheme based on these two models. This dialogue clarifies knowledge gaps, refines queries, and generates new knowledge through interactions with the system.

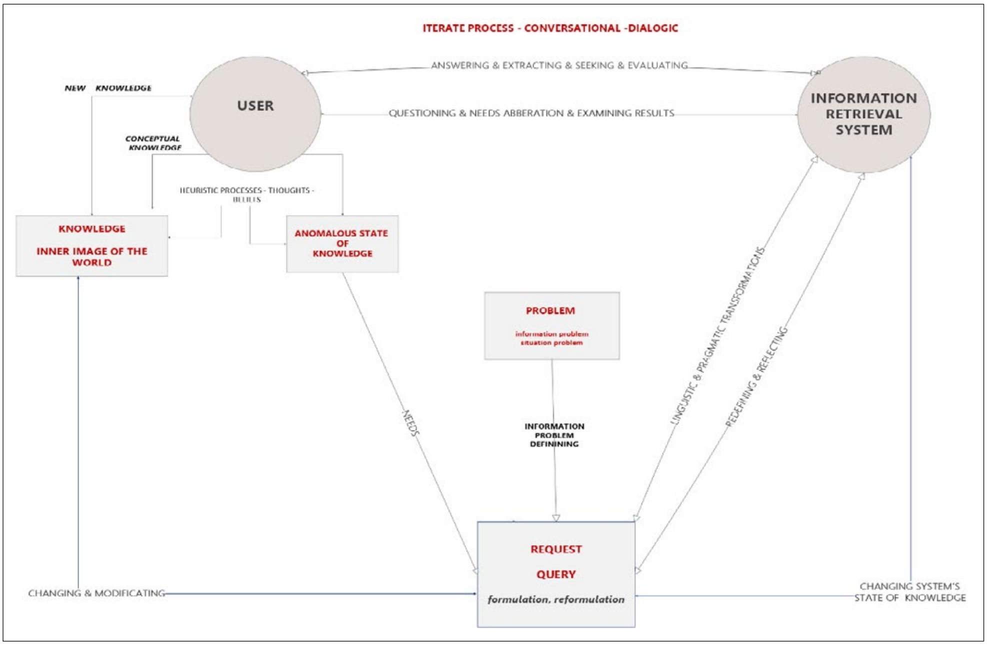

Fig. 1. Proposed model of information-seeking models
based on Nicholas Belkin & Garry Marchionini
(Belkin & Marchetti, Cole, 1993; Belkin et al., 1995; Marchionini, 1995).

Source: self-authored.

Information-seeking involves engaging with texts to interpret and solve problems, often within systems like IR systems. Prompts can guide this process, framing the user's query to help refine their search. Dialogic information seeking, where users and systems interact in an ongoing exchange, allows for dynamic prompts and responses that adapt to users' evolving needs, improving the efficiency of finding relevant information.

2.2. Prompts – definitions

In the context of generative artificial intelligence (GenAI), a prompt is a means of communication between a user and a Large Language Model (LLM) that enables the user to guide the model appropriately when generating a response (McNulty, 2024; Springs, 2024; Srinivasan, 2024). The message the user provides may be in the form of written text, an oral message, and visual and audiovisual objects. Similarly, the generated response may present itself in the form of linear written text or multimodal text.

GenAI, a branch of artificial intelligence (AI), is based on machine learning (ML) generative LLM models, a subset of artificial neural networks (ANN). These models generate content from user prompts (Sahoo et al., 2024; Zhang, 2024), with examples including ChatGPT, Midjourney, DALL-E, and Microsoft Copilot (Akakpo, 2024; Hassani & Silva, 2024; McNulty, 2024). Key terminology associated with GenAI includes "prompt engineering" (PE), "prompt tuning," and "prompt design." PE, the most general term, optimises user-AI communication, whether manual or automated (Huang et al., 2024; Mudadla, 2024), combining elements from AI, linguistics, and user experience (Lo, 2023). It guides language model predictions without altering model weights (Srinivasan, 2024) and focuses on designing prompts for optimal AI interpretation (Greyling, 2023; Lund, 2023). PE is considered an essential skill that merges language, logic, and creativity (Springs, 2024; Zhou, 2023), forming part of both AI and information literacy (Lund, 2023; McNulty, 2024). Some also regard PE as an art form (Frederick, 2024), with variations like "prompt answer engineering" (Huang et al., 2024) and "GPT engineering" (Springs, 2024) specific to ChatGPT prompts.

Prompt design, a key element of prompt engineering (PE), involves creating and optimising user instructions in natural language to elicit specific AI responses (Mudadla, 2024). PE also includes prompt tuning, which focuses on crafting prompt templates for particular tasks and learning selected parameters (Srinivasan, 2024). However, models using prompt tuning tend to be less stable and specialised in specific tasks with limited general knowledge (Shi et al., 2024; Spathis & Kawsar, 2024). "Prompt writing" outside the academic context involves creating inputs to guide AI outputs (McNulty, 2024). Additionally, "prompt pattern" outlines the structured components of a prompt for generating coherent and relevant text

(Marques et al., 2024), while “prompt template” is a static format where variables can be substituted (Greyling, 2023; Vogel, 2024).

2.3. Overview of how to write prompts: elements, writing style, typologies

The general rules for writing prompts are undergoing a period of adjustment as AI models and their capabilities continue to evolve. Some rules may appear logically inconsistent if viewed as a universal solution applicable to all AI models and tasks. For instance, negation, typically discouraged (Ruksha, 2024), is nevertheless observed in Negative Prompting (Aryani, 2023).

The typical components of a prompt include an agenda that provides task context (McNulty, 2024; Springs, 2024; Srinivasan, 2024), instructions describing the task (Springs, 2024), a trigger offering specific examples for the AI to develop (Springs, 2024; Srinivasan, 2024), and the format for the response, including handling exceptions (Springs, 2024; Srinivasan, 2024). This list is illustrative and not exhaustive, as no definitive set of prompt components exists. Frameworks like AUTOMAT, CLEAR, CO-STAR, and RICCE offer guidance on structuring prompts, with AUTOMAT being the most comprehensive. AUTOMAT includes seven elements: defining the AI’s role, audience, action, output format, style, handling exceptions, and setting topic boundaries (Vogel, 2024). Precision in prompt language is crucial, balancing clarity with flexibility to allow for AI creativity (Lynch et al., 2023; McNulty, 2024). Simplicity in language and breaking complex tasks into steps improve results (Srinivasan, 2024; Vogel, 2024). Avoiding biased terms and using proper punctuation further enhance the effectiveness of prompts (Patel, 2024; Warraich, 2024).

Academic and professional literature identifies various approaches to writing prompts, such as strategies, methods, techniques, patterns, templates, and formulas, though their organisation lacks consistency (Ruksha, 2024). In AI models like ChatGPT, communication can occur via a user interface or API (Sufi, 2024). Prompts are also categorised as hard or soft. Written in natural language, hard prompts are static and associated with prompt design, often using templates (Greyling, 2023). Soft prompts, generated through prompt tuning, adapt to data and the model, undergoing a learning process (Greyling, 2023; Zixuan Yi et al., 2024).

Furthermore, prompts can be classified according to the number of examples provided in the message. That is referred to as N-Shot prompting (Corral, 2023). This perspective distinguishes between Zero-Shot, One-Shot, and Few-Shot Prompting based on the number of examples provided. However, complex prompts may involve multiple variants at different stages of interaction with GenAI.

In addition to the aforementioned typologies, K. Ruksha’s (2024) proposal is worthy of note. It applies to the entire field of PE and distinguishes between (1) Single Prompt Techniques, which approach aims to obtain a maximally useful response with a single, optimised user query; (2) Multiple Prompt Techniques: this approach combines different prompts and assumes that a dialogue with the AI will be carried out through successive iterations; (3) the application of external communication tools in interaction with the LLM, including RAG and ReAct.

In the corpus of literature analysed, references to Chain of Thought (CoT) were most common (see Figure 2). Indeed, this is one of the most well-known ways, and it is combined especially with various variants of N-Shot-Prompting. Various advanced prompts and further variants of prompt writing are also based on CoT. Due to its versatility and popularity, CoT was used in the case study. For a more detailed description of the CoT in relation to the scientific literature search task and the information behaviour models analysed, please see the case study section.

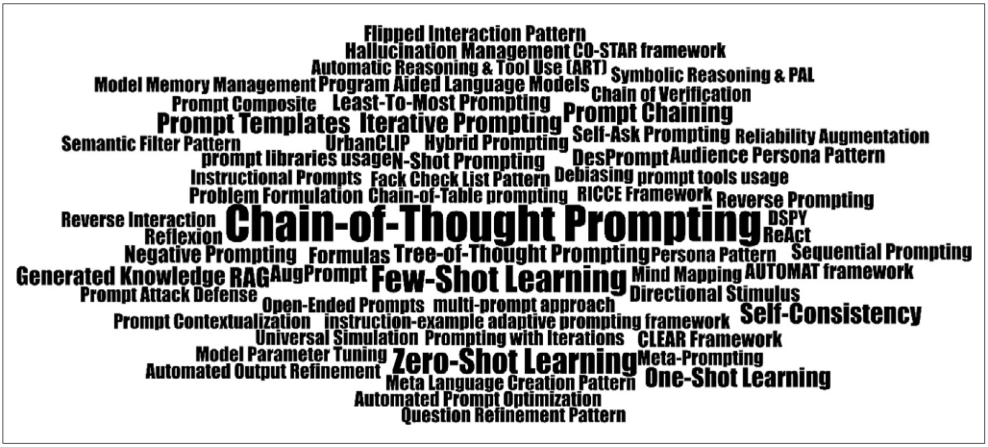

Fig. 2. MAXQDA code cloud showing specific ways to write prompts in PE.

Source: self-authored.

Given the numerous approaches to writing prompts, each with distinct characteristics in response generation, choosing one that aligns with the specific problem and the GenAI model's capabilities is essential. Possible GenAI prompts include: web page analysis (Hall & McKee, 2024), content classification (Chen, S. et al., 2024; Huang et al., 2024; Marques et al., 2024; Shi et al., 2024; Song et al., 2023), social media content creation (Hall & McKee, 2024), evaluation criteria development (Hall & McKee, 2024), data analysis and visualisation (Hall & McKee, 2024; Hassani & Silva, 2024; Sufi, 2024), learning materials development (Hall & McKee, 2024), forecasting (Hassani & Silva, 2024), idea generation and brainstorming (Hall & McKee, 2024), narrative generation (Lynch et al., 2023), synthetic dataset creation (Litake et al., 2024; Lynch et al., 2023; Sufi, 2024), keyword identification (Zhang, 2024), literature search assistance (Zhang, 2024), reasoning (Chen, S. et al., 2024), requirements elicitation (Marques et al., 2024), content review (Hall

& McKee, 2024; Marques et al., 2024), academic article hint searching (Zhang, 2024), sentiment analysis (Lynch et al., 2023), and programming code writing (Hall & McKee, 2024; Marques et al., 2024).

Concurrently, the academic literature identifies categories of problems for which GenAI models are considered inadvisable. Such categories of problems include, but are not limited to, the following: the analysis of private information or data (Hall & McKee, 2024); the analysis of current events (Hall & McKee, 2024); the citation of sources (Hall & McKee, 2024); and the analysis and visualisation of data. Furthermore, the analysis of complex data (Hall & McKee, 2024), as well as fact-checking (Hall & McKee, 2024), is problematic, as evidenced by the difficulty of answering tricky questions from the examples provided by Mariusz Pisarski (2024, p. 234). Some of the discouraged tasks are inconsistent with the list of problems that GenAI was used to solve. That is particularly relevant in the context of forecasting, which involves the analysis of current events and the visualisation of complex data. Furthermore, caution should be exercised when searching for scientific literature and citing sources due to the hallucinatory nature of GenAI models.

3. Research goals

The primary purpose of this article (A1) was to identify and describe the theoretical and practical foundations of PE in information science, focusing on well-established dialogic/conversational information retrieval models. The premise of this paper is that information science has long been concerned with issues currently being applied to the development of PE. A particular and most obvious area is human-machine interaction, mainly through dialogue/conversational systems. An additional aim (A2) was to identify possible further areas of commonality between information science and PE and, consequently, to identify well-established achievements in information science from which PE researchers and practitioners can benefit and other research fields for joint development within both disciplines.

Two principal research questions have been identified as particularly relevant to the aforementioned objectives. Research question RQ1 is linked to main objective A1 and consists of four extended subquestions (RQ1.1–RQ1.4). RQ2 is derived from the secondary research aim A2.

- RQ1. What are the relations between the dialogic/conversational models of information seeking well established in information science and the way prompts are written in PE?
  - RQ1.1. What are examples of dialogic/conversational information-seeking models established in information science? What elements do these models comprise? How does the human-machine conversation work in these models?

  - RQ1.2 What are the ways of writing prompts in PE? What elements can prompts consist of? What does it mean for a human to communicate with a GenAI model using prompts? What are the limitations of prompt communication with GenAI? In which problem situations are ChatGPT-type GenAI models used?
  - RQ1.3. What are the similarities between the well-established dialogic/conversational models of information seeking in information science and human communication with GenAI via prompts?
  - RQ1.4. What are the differences between the dialogic/conversational models of information seeking well established in information science and human communication with GenAI using prompts?
- RQ2. Beyond human-machine communication through dialogic/conversational models of information seeking/retrieval, are there common research areas between information science and PE? If so, what are these areas?

Given the ongoing development of GenAI models, the research questions relate to the current state of PE, understood as 2024 and the ChatGPT 4o model.

4. Methodology

The article presents the results of a qualitative strategy (Nowell et al., 2017) comprising a critical literature review (Cisek, 2010) and a case study.

A critical literature review was conducted to determine the extent of literature on PE and possible links to information science and information behaviour. In order to collect relevant academic and industry-related literature, a preliminary literature search was carried out on September 3rd 2024 to identify the topic area and obtain an initial list of keywords using Semantic Scholar (AI-based) and the Medium service (https://medium.com/). Keyword searches were used: a) in the case of Medium, the search was performed from within Google using an instruction consisting of a site command to search within the domain and the keyword prompt (site:medium.com prompt), and b) in Semantic Scholar, the term prompt was searched. 510000 results were extracted from the Semantic Scholar database, sorted by relevance, and the first 10 pages of the results table were examined. The Semantic Scholar material was only used to gain an initial understanding of PE terminology.

Subsequently, on September 8th, 2024, a search was conducted in the LISTA database to extend the search to information science publications. The search consisted of three phases. The first phase of the search used the phrase: (DE 'INFORMATION-seeking behaviour' OR DE 'INFORMATION needs' OR DE 'INFORMATION-seeking strategies' OR 'information seeking' OR 'information literacy' OR 'information behaviour' OR 'information seeking' OR 'information literacy' OR DE 'INFORMATION literacy') AND ('prompt engineering' OR 'prompting'

OR 'generative AI'), resulting in 26 publications. The search term 'prompt engineer*' was used in the second phase of the LISTA search, yielding 21 publications. In the third phase, the combination of the phrases 'prompt* tuning' OR 'prompt* method*' OR 'prompt* technique*' OR 'prompt design' OR 'prompt* pattern*' OR 'prompt AI' OR 'prompt artist*' yielded 14 results. A total of 59 results were included in the literature analysis and critique: a). from LISTA searches (within stages 1, 2, and 3 and after elimination of duplicates): 40 publications; b) from Medium: 19 professional articles.

All retrieved publications were then uploaded into MAXQDA. The use of MAXQDA streamlined the analysis and critique of the literature as it allowed for the efficient collection of sequential readings in a single environment and allowed for the highlighting and coding of content related to the subject of the study. The analysis sought to answer the following questions:

(1) How are prompts and related terms defined?
(2) How are prompts written (general principles, elements and types of prompts, limitations of PE)?
(3) Who is involved in writing prompts, and what competencies are associated with PE?
(4) What are the links between PE and information science?
(5) What are the areas of application of prompts outside information science?
(6) What tasks are PE used to solve?
(7) In what problem situations is PE not recommended?

These seven questions were assigned to the MAXQDA codebook (229 codes were obtained).

5. Case study: collecting scientific literature on a given topic (research on immersion in the virtual reality (VR) environment)

In the case study, a scientific literature search task was selected. The objective was to identify publications that were relevant to the problem situation. That is one of the tasks for which prompts have been employed (see, for example, Zhang, 2024). The challenge lies in both the complexity of the process of selecting appropriate literature that meets certain content and formal criteria and the limitations of LLM in the form of hallucination. In the case described here, the problem was related to scientific publications in immersion research in VR environments.

The conversation with ChatGPT (model 4o) was initiated by clearing memory (see excerpt one in Fig. 3). After consideration of the available options for formulating prompts, it was determined that the Multiple Prompt approach would be most suitable. It captures the complexity of the user's interaction with information systems by assuming that it is possible to converse with the GenAI model based on successive iterations, through which the essence of the information need – for both the user and the system – is more clearly captured.

The initial prompt emphasised the need to justify the selection of literature, prompting the use of Chain-of-Thought (CoT) to ensure the model provides a sequential rationale for each step (Ruksha, 2024). CoT can also be combined with multiple examples in instructional contexts, aiding in developing complex prompts. By clarifying the response formulation process, CoT enhances the transparency and coherence of LLM responses (Sahoo et al., 2024). Additionally, literature analysis (see Figure 2) shows that CoT is widely used for prompt writing. It is a key method for exploring links between modern prompt techniques and dialogic information retrieval models.

In the case study presented here, a request for justification was employed, along with an illustration of a potential approach to selecting subsequent publications. Additionally, a reminder was provided to act following the sequential execution of steps. Typically, the CoT is explained with relatively straightforward mathematical examples. However, the essence of the task at hand is more complex. Nevertheless, it can still be described with a CoT by breaking the task down into smaller scopes (identifying thematic areas such as theoretical foundations and practical considerations of the research (excerpt three in Fig. 3) and listing specific aspects to specify the topic (8)), presenting the expected way of justification and encouraging step-by-step thinking (9).

In order to represent the problem situation as accurately as possible, an AUTOMAT framework was employed (see excerpts 2-8). That allowed a detailed description of the thematic scope of the search to be provided, the user's initial competence to be defined (3), and a specific response format to be indicated (5, 7). Moreover, it was assumed that the information need may be dynamic and not fully conscious or explicit in the user's mind. Therefore, an approach was adopted to enable ChatGPT to facilitate the user in articulating the essence of the information need more effectively. Accordingly, an interview pattern (Cangiano, 2023) was employed, through which the GenAI model was instructed to conduct an information interview with the user and incorporate the extracted responses into the final information product generated by the AI. This approach was initiated with the command "interview me" (10). Consequently, ChatGPT guided the user with a series of questions to enhance comprehension of the problem situation (see excerpt 11 in Fig. 4).

In the dialogue shown in Figures 3 and 4, ChatGPT provided three outcomes with justifications and availability of data for "Theoretical Foundations" and "Practical Implementation of Virtual Reality (VR) User Research." No publications were fabricated, and the answers followed the specified outcome format (5). Figure 5 displays an example publication in APA format, with a numbered list and accessibility information. While the DOI link did not redirect to the full text, free access was confirmed via Google Scholar. A brief justification for the suggestion was included. Additionally, ChatGPT offered a section on "Practical Aspects for Organising Research with VR Users," covering lab setup, think-aloud protocols, observations, surveys, and data recording. The full chat is accessible at: https://chatgpt.com/share/66fe483d-47b0-8009-8090-ca499a1a2ed9 (accessed October 4th, 2024).

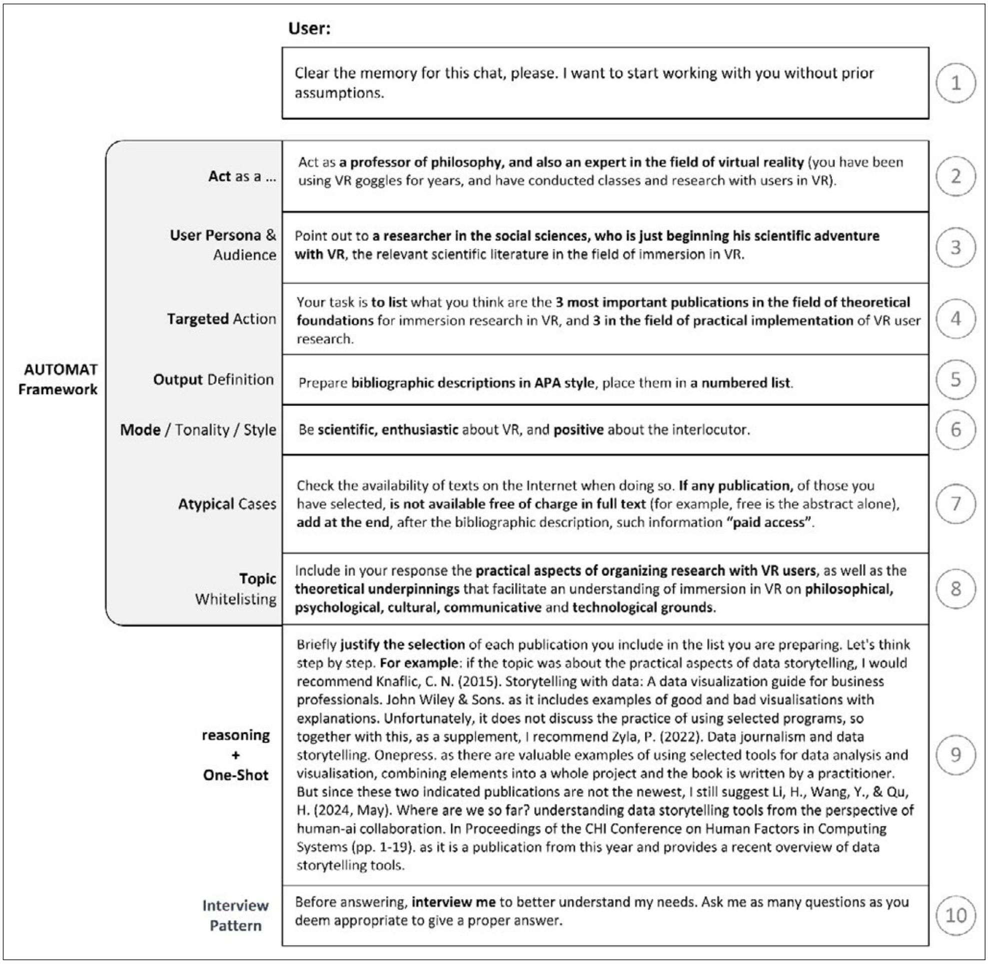

Fig. 3. Initial prompt structure (ChatGPT 4o).

Source: self-authored.

ChatGPT 4o:

That sounds like a fascinating research journey you're embarking on, and I'm excited to help guide you through the immersion aspect of virtual reality (VR)! To better tailor the literature recommendations and make sure I understand your needs, let me ask you a few questions:

1. **Research Focus**: Are you primarily interested in how immersion is experienced psychologically (e.g., presence, flow) or more in terms of technical and cultural frameworks?
2. **Discipline**: In which social science domain is your research grounded? (e.g., psychology, sociology, anthropology, communication studies, etc.) Knowing this will help me pinpoint theoretical frameworks relevant to your discipline.
3. **Research Approach**: Are you looking to focus more on experimental designs (e.g., measuring user reactions) or qualitative methods (e.g., interviews, ethnography)? This will help me choose publications that best fit your methodological preferences.
4. **Level of Expertise with VR Tools**: How familiar are you with current VR systems, software, and technical aspects of conducting research (e.g., hardware specs, user interface designs)? Do you need beginner-friendly implementation resources, or are you looking for more advanced material? 11
5. **Research Environment:** Will your VR research be conducted in a controlled lab setting, or are you planning to work with users in real-world or field settings? This can influence the choice of practical literature.
6. **Access to Paid Sources:** Would you prefer open-access resources, or are you okay with using publications that require paid access? I will prioritize open-access content if that is important to you.

With answers to these questions, I can ensure the publications I recommend will suit your focus and needs. Let me know!

User:

Thanks for these questions - they're already useful on their own. I've got the answers for you right here:
1. I am currently only interested in the psychological, cognitive, affective aspects. Skip the technological aspects.
2. social communication and media studies, especially information science
3. focus on qualitative methods, but including research in VR (respondents experience VR using goggles) 12
4. I privately use VR goggles but have not conducted UX research in VR, I have previously done research using e.g. think-aloud protocol, observation, surveys, heuristics analysis, but not in a VR environment
5. lab setting,
6. i need mostly free (max. 1 can be paid)

Fig. 4. ChatGPT user interview (a follow-up, ChatGPT 4o).

Source: self-authored.

ChatGPT 4o (sample answer):

Theoretical Foundations

1. Slater, M. (2009). ***Place illusion and plausibility can lead to realistic behaviour in immersive virtual environments***. Philosophical Transactions of the Royal Society B: Biological Sciences, 364(1535), 3549-3557.
   DOI: https://doi.org/10.1098/rstb.2009.0138
   Availability: Free access.
   Justification: Slater is one of the most cited researchers in VR immersion, and this paper introduces his influential theory of "place illusion" and "plausibility illusion" as two core aspects of immersion. It is essential reading for understanding the psychological experience of "being there" in a virtual space. This helps you frame users' cognitive responses to VR environments.

Fig. 5. A single publication record from the ChatGPT response (ChatGPT 4o).

Source: self-authored.

6. Discussion

Examining dialogic information-seeking models reveals apparent interconnections with established conversational information-seeking and retrieval frameworks (RQ1). The dialogic process conducted with ChatGPT, alongside using the CoT and AUTOMAT frameworks, highlights how reasoning and query refinement are iteratively managed. This process supports transparent interactions with the system and facilitates the retrieval of relevant responses. The steps taken by the system were clarified, including the formulation of answers and the breakdown of tasks and information problems into more detailed stages. This approach effectively addressed the user's knowledge gaps, allowing the concretisation of information needs and the creation of new knowledge. By applying filters and narrowing information retrieval pathways, queries were precisely specified, directing knowledge retrieval. The system's reasoning modes were clarified, resulting in a tailored interaction. The system encouraged ongoing dialogue, enabling users to submit reusable requests regarding queries, topics, and analytical approaches. That led to a flexible, multifaceted conversational process focused on information seeking and retrieval. The case study highlights the AI model's ability to deepen discussions and precisely redirect literature searches, as demonstrated in the Interview Pattern phase (excerpt 12 in Figure 4). It is crucial to verify the information provided by ChatGPT, as hallucinations may occur even if they were absent initially. Techniques like providing sources in a specified format with active links or DOIs have been implemented to aid in information verification. The completeness of ChatGPT's results is a separate issue and will be explored in future studies.

The AUTOMAT framework refers to Belkin's and Marchionini's models of information extraction processes (see Fig. 1) and incorporates virtually the same components and processes. It also highlights the numerous activities that the user and the system must undertake to clarify, redefine, and transform the user's information needs expressed through the questions asked, representing a continuous, iterative, planned and creative way of extracting relevant answers from the system. The request to clear memory during the start of the dialogue with the system (see excerpt one in Fig. 3) became the basis for removing previously accumulated knowledge, pre-remembered assumptions, the way the user usually formats the result, bridging the user's cognitive bias and leaving the generator's image of the world unconstrained by conditions previously suggested by the user. The heuristic processes undertaken during the recognition of the information need, the user's conceptual state of knowledge, highlighted by Nicholas Belkin and Garry Marchionini, were taken into account during stages 2 and 3 (see Fig. 3). The objective was to prompt the system to envisage the user and the circumstances under which the problem is to be solved, for example, by utilising virtual reality goggles. Subsequently, a persona was constructed, delineating the context of functioning and the performance of a particular task. This information constituted the problem statement. Clarifying the context and problem situation proved instrumental in defining the task correctly and concretely, as well as fostering awareness of the inherent complexity of the information need. That formed the basis for developing a reformulation of requests and queries per the AUTOMAT framework. The concretisation of the task to be performed by the system (see excerpts 4 and 5 in Fig. 3) facilitated the clarification of queries and the linguistic and pragmatic transformation of the user's thoughts and conceptual knowledge about the information need and information problem. The anthropomorphic format of the dialogic process of information retrieval in relation to the mode or style of the expected replica of the system (see excerpt 6 in Fig. 3) considered the processes of understanding how the user communicates with the machine and how the machine can also take into account its modes of communication. That allowed the construction of the affective and cognitive context of the situation. The "Atypical cases stage" (see excerpt seven in Fig. 3) correlates with the extracting, iterating and reflecting processes, whereby the user's information need is further specified, thus influencing the expected actions of the system in relation to the extracted results.

Part 8 of the framework (see Fig. 3) defines the complexity of the information problem and helps reframe queries based on the user's knowledge. A detailed description of the information need drives the system to perform the search. In the Reasoning + One-Shot trials (see excerpt nine in Fig. 3), methods for information retrieval were refined, especially given ChatGPT's limitations with negation. Users guide the system on how to explain, reason, and deduce, which aids in clarifying their knowledge, identifying gaps, controlling the retrieval process, and evaluating results. The concretisation and iterative formulation of queries during the conversation serve to comprehensively alter the knowledge of both the user and the system. This results in a change of state of knowledge, the creation of new knowledge, and new ways of information seeking.

The final phase of the prompt framework invites dialogue to detail the information problem and needs (see excerpt 10 in Fig. 3). The interaction between the user and ChatGPT refined the extraction of relevant results. ChatGPT's questions (see excerpt 11 in Fig. 4) helped adjust the information needs, clarify the problem's context, and guide the user in forming new queries. Questions about the research focus, approach, and user competence (persona) were crucial for understanding the issue and modifying the system's retrieval pattern. The responses (see Part 12 in Fig. 4) helped define the persona, search domain, and extract results. The iterative process of questioning, answering, and seeking, based on Belkin's and Marchionini's models, was integrated into prompt engineering formats like AUTOMAT, CoT, and Interview Pattern. These elements highlight the parallels between prompt engineering and established information-seeking models. The contemporary framework addresses need definition, query formulation, and reasoning refinement, incorporating cognitive processes into the AUTOMAT framework.

7. Conclusions and limitations

The analysis irrefutably revealed the components, modes of reasoning and conversation, processes and relationships between the dialogic/conversational models of information retrieval that are firmly established in information science and the way of writing prompts (RQ1). The selected models from information science are not recent, but they are indisputably well-established, described and used in further analyses. They provide a strong foundation for developing information retrieval models during prompt engineering. Furthermore, they align perfectly with existing, contemporary schemes and frameworks developed for writing prompts. This paper outlines the various dialogue models developed in information science and how a conversation is established between humans and computers (RQ1.1). We have identified the most important requirements, including prompt writing, limitations, and the meaning of this relation in human-computer communication, especially with GenAI and its application in ChatGPT (RQ1.2). The case study and conversation with a user demonstrated how contemporary information retrieval formats and selected models from the field of information science can be linked and how they differ (RQ1.3 and RQ 1.4). The models analysed and compared account for the anomalous state of knowledge, the iterative nature of the process of acquiring information, the dialogic nature of human-computer interaction, the refinement of the information problem by reformulating queries, their processing dynamics by the user and the system, and the creative nature of knowledge creation based on extracting, needs abating, and examining results.

It is important to acknowledge the limitations of the study. The study focused on specific models and methods of prompt writing. The rationale behind the selection is clear, but additional options could be considered in subsequent research projects. The same is true concerning the selection of the specific problem situation. It would be wrong to extrapolate the example from the case study to all potential scenarios related to information retrieval and using prompts. The description of the state of PE presented in the article pertains to the ChatGPT 4o model, which constituted the latest publicly available model at the time of the research. Subsequent GenAI models will undoubtedly offer new or enhanced functionality. This article has demonstrated the links between information science and PE in their current state of development. In light of potential future GenAI models, an update in the form of further research is necessary.

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Sztuka prompt engineering jako stara/nowa forma dialogowego poszukiwania informacji z wykorzystaniem modeli sztucznej inteligencji

Abstrakt

Cel/Teza: Artykuł syntetyzuje teoretyczne i praktyczne rozważania na temat komunikacji dialogowej z sztuczną inteligencją, koncentrując się na uznanych modelach wyszukiwania informacji. Bada interdyscyplinarny charakter badań nad zachowaniami informacyjnymi oraz ewolucję modeli wyszukiwania.
Koncepcja/Metody badań: Zastosowano metodologię jakościową, obejmującą krytyczną analizę literatury oraz studium przypadku wykorzystujące ChatGPT do wyszukiwania literatury naukowej.
Wyniki i wnioski: Analiza ujawniła współzależności między tradycyjnymi a nowoczesnymi modelami, podkreślając poznawcze i eksploracyjne aspekty wyszukiwania informacji.
Ograniczenia badań: Skoncentrowano się na specyficznych modelach prompt engineering oraz jednym studium przypadku.
Zastosowania praktyczne: Zrozumienie uznanych modeli jest kluczowe dla rozwoju prompt engineering.
Oryginalność/Wartość poznawcza: Niniejsze badanie wypełnia lukę w badaniach nad integracją modeli wyszukiwania informacji z prompt engineering.

Słowa kluczowe:

ChatGPT. Konwersacyjne wyszukiwanie informacji. Model wyszukiwania informacji. Podejście dialogowe. Prompt engineering (PE). Sztuczna inteligencja (AI). Wyszukiwanie informacji.

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